Instrumental Movements of Neophytes

Analysis of Movement Periodicities, Commonalities and Individualities in Mimed Violin Performance

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Abstract. Body movement and embodied knowledge play an important part in how we express and understand music. The gestures of a musician playing an instrument are part of a shared knowledge that contributes to musical expressivity by building expectations and influencing perception. In this study, we investigate the extent in which the movement vocabulary of violin performance is part of the embodied knowledge of individuals with no experience in playing the instrument. We asked people who cannot play the violin to mime a performance along an audio excerpt recorded by an expert. They do so by using a silent violin, specifically modified to be more accessible to neophytes. Preliminary motion data analyses suggest that, despite the individuality of each performance, there is a certain consistency among participants in terms of overall rhythmic resonance with the music and movement in response to melodic phrasing. Individualities and commonalities are then analysed using Functional Principal Component Analysis.

Keywords: Movement, gesture, body motion, motion capture, violin, musical instrument, performance, motion analysis, Periodic Quantity of Motion.

1 Introduction

The study of embodiment, body movement and gestures in music has recently become an established field of study. Several theoretical accounts have been put forward through the years [16, 20, 18, 17], often accompanied by empirical analysis of body movements of people performing, listening or dancing to music.

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As pointed out in [26], musical instruments have a *a repertoire of sound-producing gestures* that contribute to build the *ecological knowledge* associated to that instrument. Hence, this shared knowledge affects one's musical experience, by creating expectations and guiding musical understanding. In fact, by adopting an ecological approach, musical perception is seen as an active experience influenced by a highly-structured environment rather than a passive, disembodied phenomenon. From this perspective *"exposure to the environment shape perceptual capacities of an individual"* and *"perception and actions are inextricably bound together"* [8].

The goal of the present study is to empirically explore the shared knowledge of the gestural repertoire of a well-known musical instrument among people that have no previous experience in playing that particular instrument. This is done by analysing the motion data gathered during an experiment where neophytes are asked to mime a violin performance. The analysis focuses on several body parts and movement features, in relation to the music and in comparison to the actual performance of an experienced violinist.

This experiment draws its motivation from the assumption that the musician encodes gestures in sound and the listener can decode particular aspects of them through corporeal imitation. As Leman notes, the listener is capable of grasping music as intended moving form and perception and understanding of musical expressiveness is based on corporeal resonance behaviour: *"Obviously the movements of the listener are not [...] the same as the movements of the player. What is more or less the same [...] is the motor system that encodes and decodes sonic forms."* [20]. Therefore, a more detailed analysis of the extent of the gestural vocabulary of an instrument also among non-experts can contribute to the understanding of musical perception and expression.

A relevant aspect of the design of this experiment is the use of an actual violin, specifically modified to not emit any sound when bowed and to be more accessible to people that have never used one before. Previous studies have analysed so-called "air performances" of experts and beginners mimicking the use of various instruments [15, 10]. Here, the choice of using an actual instrument is motivated by the adoption of an ecological approach, assuming that the relationship with the object (indeed part of the aforementioned environment [8]) and its affordances [13, 12] may have a significant impact on the movements of the subjects. In addition, experience using tools has also been the subject of embodied music cognition research [21] and the concept of affordance has seen renewed interest in multidisciplinary music research [23, 1].

The analysis of the motion data gathered during the experiment focuses prevalently on intermediate and high-level movement descriptors. This is motivated by ecological perceptual theories suggesting that, when processing information, people seem to be aware of high-level features more directly than lower-level features [8]. Therefore, we expect high-level movement features to be more readily identified and shared by the participants. Moreover, body movement and entrainment in response to music are complex and dynamic phenomenons. Therefore, movement analysis should try to address complex patterns from multidimensional motion data, rather than single values that capture a particular feature of a movement segment. Amelynck et al. [2] proposed a new method that avoids this segmentation and takes into account the complete movement dynamics. They analysed the spontaneous bodily responses of people to a musical stimulus and tried to model expressiveness in terms of commonalities and individualities using Functional Principal Component Analysis (FPCA) [25].

2 The Experiment: Material and Methods

2.1 Participants

A total of thirteen participants took part in the study. This includes twelve neophytes (7 male, 5 female, average age: 33.4, SD of age: 9.8) and one experienced violinist (male, aged 23), who performed and recorded the stimuli for the experiment. All participants gave their informed consent and were free to take breaks or abandon the experiment at any point. Ethical approval was granted by the Arts and Humanities Research Ethics Sub-committee at the Faculty of Arts and Humanities, Plymouth University. Participants were also asked to fill out a brief anonymous questionnaire with basic personal data and information about their musical background.

2.2 Stimuli

Participants were asked to mime a violin performance using the modified violin along 5 randomly-ordered musical stimuli, which consisted of brief solo violin excerpts recorded by the experienced violinist. Stimuli were between 8.5 and 34 seconds long and were chosen to cover a variety of different styles and instrumental techniques.

List of Stimuli

– Antonio Vivaldi *"Violin Concerto in A minor, Op 3, No 6, RV 356"* (1711)
– Camille Saint-Sans *"Le Carnaval des Animaux - 10. Volire"* (1886)
– Kaija Saariaho, *"Nocturne for solo violin"* (1994)
– Niccolò Paganini *"Caprice No. 1 'The Arpeggio' in E major: Andante"* (1819)
– Sergei Prokofiev *"Five Melodies for Violin and Piano, Op. 35bis"* (1925)

This first study focuses on the data collected using the first stimulus, which consists of the first twelve bars of the first movement (Allegro) of Vivaldi's Violin Concerto in A minor (Fig. 1).

Fig. 1. Excerpt of the the violin part of Vivaldi's Violin Concerto in A minor. The audio recording of the first twelve bars was used as stimulus for the experiment.

2.3 Apparatus

The multimodal recordings were carried out at the Interdisciplinary Centre for Computer Music Research (ICCMR), Plymouth University, United Kingdom and at fourMs - Music, Mind, Motion, Machines, University of Oslo, Norway. In Plymouth, participants' movements were recorded using a six-camera marker-based optical motion capture system (Natural Point Optitrack Flex 3[4]) tracking at a frame rate of 100 Hz. A total of 33 reflective markers were attached to each participant and to the instrument and were located as follow[5]: LF head, RF head, LB head, RB head, L shoulder, R shoulder, spine (T5), LF hip, RF hip, LB hip, RB hip, L elbow, R elbow, L wrist (radius), L wrist (ulna), R wrist (radius), R wrist (ulna), L knee, R knee, L ankle, R ankle, L heel, R heel, L toe, R toe, R scapula[6], violin scroll, violin L upper bout, violin R upper bout, violin L lower bout, violin R lower bout, bow tip, bow frog (see Fig. 2).

In Plymouth, an additional marker located on the sternum of the participants was used. However, the data associated to that marker was eventually discarded as it contained too many dropouts due to the frequent occlusion caused by the right arm during bowing movements. That marker was therefore not used in the subsequent recording sessions in Oslo.

The stimuli were played back using a pair of Genelec 8020C loudspeakers using a DAW[7] sending a stereo audio signal to an audio interface which was used to generate the SMPTE signal used for synchronising audio, video and motion capture sources. The audio in the room was recorded by a pair of condenser microphones placed in a XY stereo configuration as well as by a video camera used to film the sessions.

[4] http://www.optitrack.com

[5] L=Left; R=Right; F=Front; B=Back. A similar configuration can be found in [4].

[6] Used to obtain an asymmetrical marker set, useful for marker identification and tracking. Not used for analysis.

[7] http://www.reaper.fm

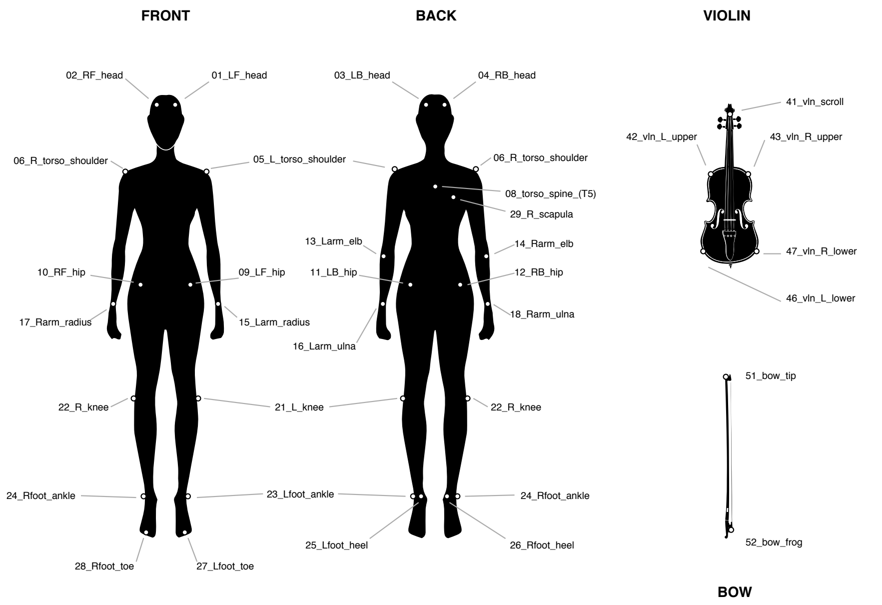

Fig. 2. Marker locations and labels.

In Oslo, the performances were recorded using a nine-camera marker-based optical motion capture system (Qualisys Oqus 300[8]) using the same frame rate (100 Hz) and marker configuration (except for the sternum marker) used in Plymouth. The feed from a digital video camera was recorded within the Qualisys Track Manager software alongside the motion tracking data. The stimuli were played back using the same model of loudspeakers and the same DAW software while recording and playback of the various sources was synchronised using a custom Max[9] patch.

The participants were asked to simulate the performance using a modified violin designed specifically for the experiment. This violin was fitted with a support system that allowed the instrument to be safely strapped to the shoulder of the participant. This was done in order to allow the participants – which in most cases never had held a violin before – to move with more confidence without being afraid to drop the instrument. Two thin metal plates soldered to a metal strip that follows the profile of the bridge were mounted on the violin body above the strings (see Fig. 3). This add-on had a dual purpose—it helped novices to quickly overcome the initial difficulties of holding the bow in a correct standard playing position and it prevented contact between the strings and the bow hair, hence making the violin silent.

[8] http://www.qualisys.com
[9] https://cycling74.com

Fig. 3. The modified violin used for the experiment.

2.4 Procedure

The expert violinist was recorded first. He performed all the selected excerpts, which provided both the audio stimuli for the neophytes and video and motion data to use as a benchmark for the analysis of the participant's movements.

Each neophyte was recorded individually. For each stimulus, the participant was asked to first listen to the audio once in order to familiarise with the music and then use the modified violin to mime a performance along the played back audio twice. Audio, video and motion data were recorded during each trial.

3 Analysis of periodicity and phrasing using Mocapgrams and Periodic Quantity of Motion

3.1 Movement Data Preprocessing

The motion data was first preprocessed, labeled and exported to C3D files using Optitrack Motive and Qualisys Track Manager. The C3D files were then loaded in MATLAB using Motion Capture (MoCap) Toolbox [5].

3.2 Comparative movement data analysis using full Mocapgrams

By plotting Mocapgrams [19] (a graph in which position coordinates of each marker are normalised and projected onto an RGB colorspace) it was possible to do a preliminary analysis and observe recurring patterns and periodicities in the motion data. Fig. 4 shows full Mocapgrams for the performances of the expert violinist and of one of the neophytes (top left and top right graphs respectively). Regular colour patterns in the horizontal rows corresponding to each marker suggest periodicity in certain parts of the body and the instrument. As an example, the thinnest pattern can be observed in the right elbow and wrist (labeled '14_Rarm_elb' and '18_Rarm_ulna' respectively), which is consistent with the pattern visible in the bow markers ('51_bow_tip' and '52_bow_frog'). This shows, expectably, a certain coherence in the movement of the bow and the arm that holds it as well as high frequency periodicity caused by the repetitive bowing movements. Similarly, it is straightforward to notice that the left toe of the expert ('27_Lfoot_toe') changes position only three times throughout the whole take at irregular intervals.

For the purpose of this study, Mocapgrams are useful not only to observe general periodicity in the movement of certain parts of the body during the performance. By providing an overall view of all the motion data, they also allow to locate movements that affect the whole body, which are visualised by vertical stripes that go across all the marker rows. The most evident perturbation in the motion data of the expert can be clearly seen between sec. 23 and 25. The waveform aligned to the graphs shows that this general shift coincides with the peak the melody reaches at the beginning of bar 9, before concluding the phrase on the minim at the end of the same bar. A similar, albeit slightly delayed[10], general perturbation in the motion data can be observed in the neophyte around sec. 25. This is consistent with the data of the majority of the other neophytes suggesting a general tendency to parse evident melodic phrases with overt body movements. As it can be noticed from the full Mocapgrams, this occurs repeatedly during the neophyte's performance and the same trend is visible in the data of the other participants. This is consistent with findings in previous studies on air-performance showing that beginners tend to move more than experts [15].

3.3 Analysis of movement periodicity using Periodic Quantity of Motion

Another useful descriptor used for analysing movement periodicity is Periodic Quantity of Motion (PQoM). First introduced in [27], this index gives an estimate of the resonance of the movement periodicity with different rhythmic subdivisions in the music. Inspired by the widely known Quantity of Motion (QoM) [6, 7], PQoM is a motion descriptor useful to observe how movement relates to rhythmic aspects of the music. PQoM is calculated by subdividing the magnitude vector of the 3D motion data into frequency components by using filter banks. The frequencies of the filters correspond to multiples and subdivisions of the musical rhythm of the piece. In this case, a frequency of 1.5 Hz corresponds approximately to a steady crotchet beat, while 0.75 Hz correspond to a minim beat, 3 Hz to a quaver beat and 6 Hz to a semiquaver beat. The PQoM at a

[10] The delay is plausibly due to the fact that the neophytes follow the audio recorded during the expert's performance, therefore their movements slightly lag behind the ones of the expert.

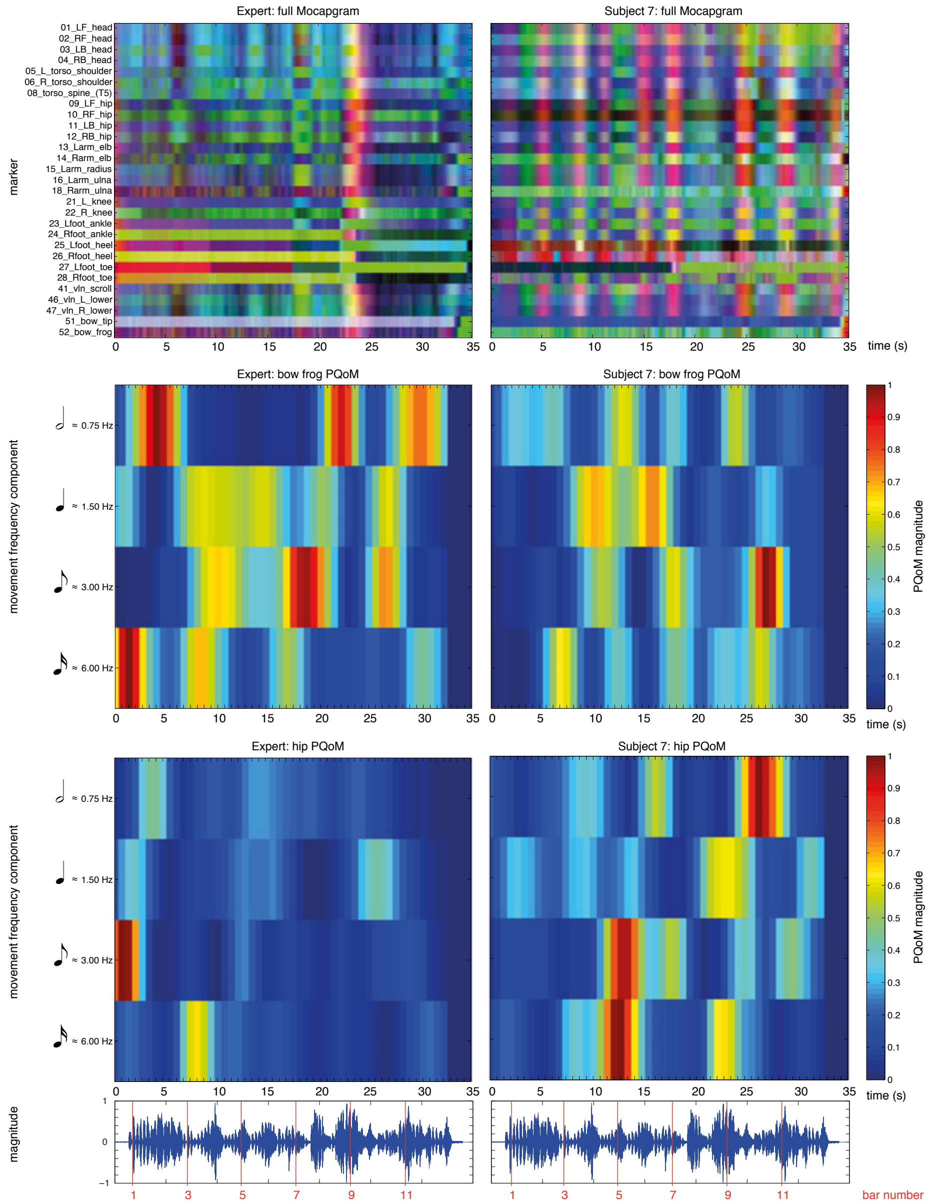

Fig. 4. Full Mocapgrams and Periodic Quantity of Motion (PQoM) estimates of the bow frog and hip markers for the expert violinist (left) and one of the neophytes (subject 7, right) aligned to the waveform of the audio. The bar numbers refer to the score in Fig. 1.

certain rhythmic subdivision is the magnitude of the corresponding frequency component in the movement normalised between 0 and 1. In this study, PQoM was estimated for four components until the end of the audio stimulus (sec. 33). By using PQoM, it is possible to relate the motion periodicities initially observed in the Mocapgrams to the actual rhythmic features of the musical stimulus. In Fig. 4, PQoM graphs of the bow frog marker and one of the hip markers (labeled 52_bow_frog and 09_LF_hip respectively in the Mocapgram) are aligned to the Mocapgrams. These two markers were chosen as the former is a good indicator of the main instrumental gesture (bowing), while the latter traces ancillary movements occurring in the lower half of the body during the performance. As shown in a previous study [26], movements in this area in some cases do not resonate evenly with the instrumental movements in the upper body. This is noticeable here as well after a first glance at the PQoM graphs in Fig. 4. Expectably, the bow frog PQoM of the expert is generally higher. However, expert and neophyte seem to follow similar patterns throughout their performances, with PQoM peaking around sec. 4 and 25 in the 0.75 Hz component, between sec. 6 and 16 in the 1.5 Hz component and at sec. 26 in the 3 Hz one. However, the two hip PQoM graphs look very different from each other, sharing only a relative peak in the 1.5 Hz component around the minim that closes the phrase in bar 9. In fact, the neophyte's hip PQoM graph shows that entrainment is remarkably more frequent and intense in that area than in the expert's. Moreover, by aligning PQoM graphs with Mocapgrams, it is possible to add further details to previous observations. In correspondence with the end of the phrase described previously (bar 9, sec. 23 – 25), there is a sudden shift of the PQoM index from a peak in the minim beat frequency to a peak in the quaver beat frequency after sec. 25. This salient turning point in the melody is therefore consistently reflected in the movement of both subjects, denoting a shared, embodied knowledge of the expressive qualities of the music, which they express through their instrumental gestures regardless of their expertise with the instrument.

3.4 Results

This preliminary comparative analysis of the motion data suggests that high-level, structural features of the music are expressed through instrumental movements in similar ways by the subjects, regardless of their ability to play violin. In particular, the turning point of the melodic phrase at bar 9 seems to be something that is *'felt'* by the subjects also in a strongly embodied way, as it impacts the movement of the whole body and the periodicity of the instrumental movements, which shifts sharply from a frequency to the other. In addition to that, after the minim that closes the phrase there is a peak in the 3 Hz PQoM of the expert and an even higher one in the neophyte. This may suggest that the suspension created by a longer note ending a phrase creates a stronger expectation for the following melodic part, with which the neophyte engages also through ancillary movements, as shown by the hip PQoM graph. In fact, all the neophytes seem to have a more pronounced full-body periodicity. This can be hypothesised by simply looking at the pink stripes in the Mocapgrams, however PQoM gives a much more precise estimate of the periodicity in relation to the musical rhythm. Nearly all the neophytes seem to have a generally higher resonance with the periodicity of the music at the hip compared to the expert, whose PQoM is instead higher at the bow frog. This may lead to hypothesise that neophytes tend to follow the pulse and the phrases of the music with ancillary movement also to compensate for the lack of expressivity of their silent instrument, hence expressing the musical content of the stimulus using their bodies.

4 Analysis of Individualities and Commonalities

Our interaction with music engages the whole body, but not all body parts show the same behaviour [3, 26]. In this analysis, we focus on the movements of the head and the right wrist. In fact, previous research has shown that string players communicate expressive qualities of the music through head movements [14, 9]. In addition, we also address the movements made by the right wrist, a body part that is directly involved in sound-producing gestures, as the bow is moved by the right hand.

In this analysis, the performances of all the 12 neophytes, are taken in consideration. Speed and acceleration were calculated from the motion data of each subject using a Savitsky-Golay smoothing filter with a regression window of 7 frames [5] and the resulting signals were set equal to the norm of the derivatives. Secondly, the speed and acceleration envelope was calculated using a moving average filter of 100 frames, to make sure the beat of the music (1,5 Hz) was covered by the window and at the same time avoid losing too much nuances in the movement. We then compared the speed of the body movements, as this feature is closely related to kinetic energy [11]. To check if the data was normally distributed, a Weibull function was fitted to the distribution of the speed values across subjects at all moments in time. The mean speed signal of the head at each timestamp over participants was approximately normally distributed, corresponding to a shape parameter of the fitted Weibull distribution of 3.12 ± 0.61 for the head and 3.04 ± 0.76 for the right wrist.

4.1 Modelling head and wrist movements

The method for the analysis of expressiveness proposed by Amelynck et al. [2] is based on Functional Principal Component Analysis (FPCA). FPCA allows to describe a signal as the sum of an average signal $\bar{f}(t)$ with a linear combination of a set of eigenfunctions $\xi_k(t)$ (commonality). Each subject can then be represented by one score (α_i) per eigenfunction (individuality):

$$f_i(t) = \bar{f}(t) + \sum_{k=1}^{K} \alpha_{ik} \; \xi_k(t) \; . \tag{1}$$

This way, the dimensionality of the problem is reduced and as much variance as possible is covered by only a small set of eigenfunctions. According to this method, the set of eigenfunctions should explain at least 70% of the variance. For our modelling, a correlation matrix based on the speed envelope of all subjects over time $C(t1, t2)$ is used as an input. An additional assumption for using FPCA is that there is a relationship between values in C that are only few samples apart. Therefore, the data is decomposed in a set of Cubic B-spline basis functions. To determine a reliable number of basis functions, the Mean Squared Error between model and signal was calculated. For both the head and wrist, the number of basis functions could be set to 60. A set of eigenfunctions could then be calculated by means of FPCA, using a least square algorithm. As the human body show complex behaviour, Varamix rotation of the functional principal component axes was considered to calculate a basis of eigenfunctions that most economically represent each individual by a linear combination of only a few basis functions. FPCA was performed using Ramsay's FDA toolbox for MATLAB. His approach [25] was followed throughout the procedure.

4.2 Results

To cover more than 70% of the variability of the head, we need up to three eigenfunctions that account for 40%, 28% and 19% respectively, totalling 87% of the variability (Fig. 5). An equal amount of eigenfunctions is needed for the wrist as 84% of the variability is covered with 40%, 15% and 29%. This means that, with only three eigenfunctions, we can model more than 80% of the commonalities in the head and wrist movements of the neophytes miming a violin performance following the musical stimulus. The individuality of each subject was obtained by calculating the Functional Principal Component Score for the three eigenvalues. The individual performance can hence be modelled by three values indicating a positive or negative score for each eigenfunction. Few individualities were required for the model, suggesting that music was embodied in similar ways among the subjects.

For the head, the first eigenfunction has a positive deviation from the group's mean for almost the entire stimulus. This means that subjects with a positive factor on this function will perform with higher speed than the average, nearly throughout the whole recording. In more detail, this eigenfunction reveals something about the periodic movement and phase of the head. Subjects scoring low on this eigenfunction will have low velocity in the beginning of the bar, and higher velocity in the middle (bars 1, 3, 4, 7, 9, 10, 11, 12), while subjects scoring high will have their velocity peak in the beginning of each bar. In the middle of bar 7, this is reversed and bar 8 and 9 have an opposite velocity profile. Note that this is the moment where the repeated note sequences end and new musical material starts. In the beginning of bar 6, the eigenfunction values are close to the mean. The second eigenfunction has a major positive deviation from the mean in bar 5,6 and 7, the second half of bar 8 and bar 9, and the last two bars. This is complementary to the first eigenfunction. The third eigenfunction has a major negative deviation, especially in the first 4 bars and bar 8.

The first eigenfunction of the right wrist has a major positive deviation in bars 2-3, 6-7 and 10-12 and the second eigenfunction accounts for a positive

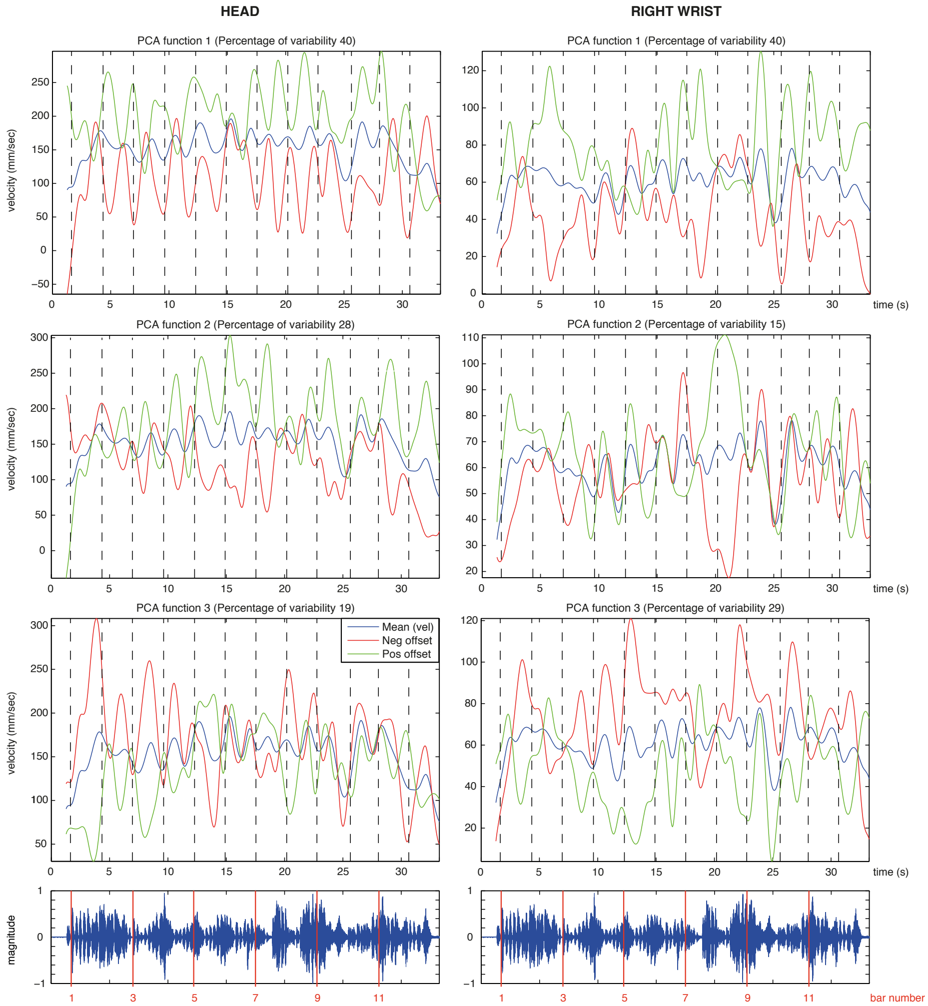

Fig. 5. Eigenfunctions for the speed envelope of head and right wrist movements after Varamix rotation. The green line indicates a positive offset from the group's mean, the red line a negative offset.

offset in bars 1 and 8 in particular. Again, the third eigenfunction has a negative deviation from the group's mean, especially covering the variability in bars 3-6, and 8-10. Fig. 6 shows the individualities for the head and wrist, clustered using k-means clustering. The number of clusters was set to 5 for the head and 4 for the wrist, after considering the optimal number with k-fold cross validation. These three variables are the principal component scores, or weights for the eigenscores, which represent the performance of the individual subject.

Some intervals of coherence (i.e. time intervals of equal signs) could be derived from these results. When an eigenfunction has multiple intervals of coherence it can be considered consistent. For the head, the first eigenfunction shows this behaviour from the middle of bar 4 until the end of bar 5, as well as from bar 7 until the end of bar 10. The second eigenfunction covers this for bars 5-7, 9, 11 and 12. The third eigenfunction does not show long intervals of equal signs, except for the first bar. Coherence for the right wrist movement is found in the first eigenfunction from bars 2-4, the middle of bar 57 and bars 11-12. The second eigenfunction reveals coherence in the first bar and from the middle of bar 7 until the end of bar 8. From bar 3 until the beginning of bar 7 and bars 8-10 are coherent in the third eigenfunction. Thus, each eigenfunction dominates specific time intervals in the musical structure and they are mostly complementary to each other. The third eigenfunction of the wrist, for example, nicely reflects the repeated notes in the music (bar 37) and the new musical material introduced in bar 8-9 and 10. A similar effect can be seen in the second eigenfunction of the head. The last two bars of the musical stimulus (11-12) are also represented in two eigenfunctions (the second eigenfunction of the head and the first of the wrist).

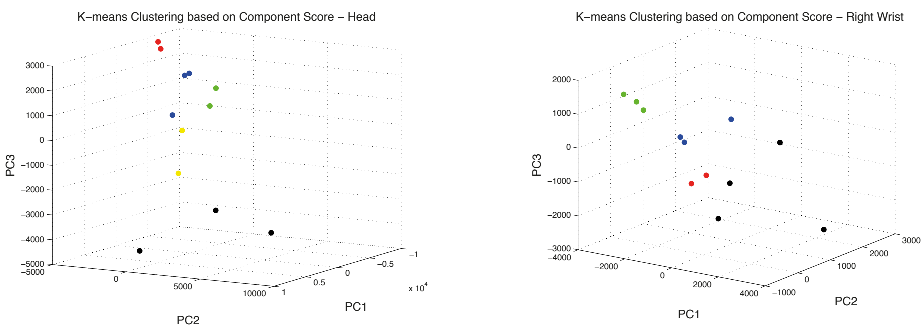

Fig. 6. Individualities for head and right wrist movements, clustered using k-means clustering.

5 Conclusion and Future Work

Even though low-level features of movement appear to vary considerably in some of the subjects, there is a certain degree of consistency among participants, especially in response to melodic and rhythmic structural features of the music. This suggests a shared knowledge of a vocabulary of instrumental movements, which is then combined with the idiosyncrasies of each subject. The analysis of commonalities and individualities confirms this, and other studies [22] support the idea that musical structure is communicated also through body movements, and idiosyncrasies contribute to express musical meaning.

Further work will go towards studying the response of the subjects also to the other musical stimuli recorded during the experiment. Each stimulus differs substantially from the other, providing material for analysis of movement in response to other musical features.

New approaches to movement analysis are in continuous development and there is an increasing need for tools that can aid the retrieval of meaningful features in complex, multidimensional motion data. Therefore, other approaches – like Topological Gesture Analysis (TGA) [24] – will be tested and possibly employed along with the methods we presented here. New techniques for motion data analysis could get inspired by concepts suggested by theories of music perception and cognition, therefore making the analysis more akin to how humans perceive and move to music. This is indeed a challenging task since retrieving meaningful, articulated information from motion data requires complex algorithms and technologies.

The PQoM algorithm will also be refined and improved for real-time implementation. This will be useful both for online analysis and interactive music performance (which was initially explored in [27]). In this study, PQoM was implemented to analyse a musical excerpt with a steady beat throughout. Since tempo in music often varies, the algorithm will be tested in order to be usable with varying tempi.

Motion data analysis has provided great detail for understanding the role of body movement in musical expression and cognition. However, it is felt that integrating quantitative data analysis with qualitative analysis and practice-based research may broaden the scope of the research, allowing to test the assumptions made through the analysis in musical contexts, outside of the sterile environment of the laboratory.

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